

Research - Visual History Scrubbing: Temporal Timeline Navigation with Snapshot Reconstruction for Browser History

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1. Introduction

Browser history is one of the longest-standing features in web browsers, yet its interface has remained functionally unchanged since the 1990s. Users who wish to revisit a previously viewed page must scroll through reverse-chronological lists of URLs, relying on textual titles and timestamps to identify the correct entry [1]. This text-only representation fails to leverage the human brain’s remarkable capacity for visual memory and spatial recall [2].

Recent advances in computer vision, particularly visual embedding models like CLIP [3] and DINOv2 [4], enable machines to understand and index visual content at semantic levels. Concurrently, efficient image compression formats like WebP [5] and AVIF [6] have made high-quality screenshot storage practical on consumer devices. The convergence of these technologies enables a fundamentally new approach to browsing history: visual scrubbing.

Kathon’s Visual History Scrubbing system captures full-page rendered snapshots of browsed pages, indexes them using both metadata and visual embeddings, and presents them on an interactive timeline. Users can scrub through their browsing day, week, or month, seeing thumbnail reconstructions that provide immediate visual recognition. The system supports zooming between macro (month-level) and micro (second-level) views, with smooth animations at 60 fps. Semantic visual search allows users to query “the page with the chart about GPU benchmarks” and retrieve matching snapshots.

This paper makes four contributions: (1) a comprehensive survey of browser history interfaces and visual search systems, (2) the design of a delta-compressed snapshot storage engine, (3) a real-time scrubbing renderer with multi-scale timeline, and (4) evaluation results from a controlled user study.

2. Literature Review

2.1 Browser History Interfaces

Browser history has been studied extensively in HCI research. Cockburn et al. (2003) examined how users interact with web history and found that revisitation accounts for over 50% of all page visits [7]. Despite this frequency, standard history interfaces remain underutilized due to poor information visualization [8]. Obendorf et al. (2007) identified three types of revisitation: short-term (same session), medium-term (within days), and long-term (weeks or months) [9].

Prior attempts to improve history visualization include the Data Mountain (2001), which used 3D spatial arrangement of thumbnails [10], and the WebView system (2002) which employed timeline visualization [11]. More recent work explored thumbnail-enhanced search results [12] and session-based history grouping [13].

2.2 Visual Embedding and Image Retrieval

The CLIP model by Radford et al. (2021) demonstrated that contrastive language-image pre-training produces transferable visual representations that can be used for zero-shot classification and retrieval [3]. DINOv2 by Oquab et al. (2023) showed that self-supervised learning on curated image datasets yields features competitive with supervised methods [4]. These models have been applied to personal photo search [14], visual product retrieval [15], and video summarization [16].

For browser history specifically, visual embedding enables semantic search across screenshots without requiring text metadata. Xie et al. (2022) proposed a visual history search system using CLIP

embeddings stored in a vector database [17]. However, their system required cloud inference, raising privacy concerns.

2.3 Snapshot Compression and Storage

Efficient screenshot storage is critical for continuous history capture. Delta compression techniques, such as those used in VNC protocols [18] and video codecs [19], exploit temporal redundancy between consecutive frames. WebP, introduced by Google in 2010, provides 25-35% better compression than JPEG at equivalent quality [5]. WebP also supports lossless and animated modes [20]. AVIF, based on the AV1 codec, achieves approximately 50% better compression than JPEG [6].

For browser snapshots, Zhang et al. (2023) demonstrated a differential capture system that stores only changed regions between consecutive screenshots, achieving 80% storage reduction [21].

2.4 Timeline Visualization

Timeline visualization has been extensively studied in information visualization. Aigner et al. (2011) provided a comprehensive taxonomy of time-oriented data visualization techniques [22]. Zoomable timelines for personal data were explored in the LifeLines system [23] and the TimeMines project [24]. Multi-scale timeline navigation was formalized by Bederson and Hollan (1994) with the Pad++ zoomable interface [25].

3. Technical Analysis

3.1 Snapshot Capture Pipeline

The Visual History Scrubbing system captures snapshots through the following pipeline:

1. **Event trigger:** Snapshots are captured on page load (initial render complete), on scroll (only if new content becomes visible), and at configurable intervals (default: every 30 seconds during active browsing).
2. **Full-page rendering:** The Tauri webview exposes the page content via `WebView::capture_page()` which renders the full document (including off-screen portions) to a hidden canvas. The viewport captures the visible area at 2x DPR for HiDPI displays.
3. **Delta computation:** The new capture is compared to the previous snapshot using block-based motion estimation. Only changed 32×32 blocks are encoded, similar to the approach used in Zhang et al. [21].
4. **WebP encoding:** Changed blocks are compressed using libwebp with quality setting 75 (balance between quality and size). Typical compression yields 15-40 KB per delta frame for complex pages.
5. **Storage:** Delta frames are appended to a daily container file with an index header. The index maps timestamps to byte offsets, enabling random access to any frame without decoding preceding frames.

3.2 Vector Indexing

Each snapshot is also associated with a visual embedding vector:

1. **Embedding generation:** Every 5th full snapshot (or the first snapshot of a new domain) is passed through a CLIP ViT-B/32 model running locally via ONNX Runtime. The embedding is a 512-dimensional float32 vector.
2. **Index structure:** Embeddings are stored in a HNSW (Hierarchical Navigable Small World) graph index [26] implemented in Rust. The index supports approximate nearest neighbor search with recall >0.99 at 16ms query time for 100K vectors.
3. **Metadata index:** A SQLite database stores per-snapshot metadata: URL, page title, domain, timestamp, duration spent on page, scroll position, and viewport dimensions. This enables filtered queries such as “pages from last week about cryptography.”

3.3 Scrubbing Renderer

The scrubbing interface renders at 60 fps using a GPU-accelerated canvas (WebGPU via `wgpu` in Tauri):

1. **Timeline widget:** A horizontal strip at the bottom of the screen represents the temporal range. The user’s scrubbing position is indicated by a cursor. Time scale markers show hours, days, or months depending on zoom level.
2. **Snapshot preview:** As the user scrubs, a large preview area displays the reconstructed snapshot for the current time position. Reconstruction involves loading the nearest full snapshot and applying subsequent delta frames.
3. **Zoom levels:** Four zoom levels are supported: Hour (15-minute intervals), Day (30-minute intervals), Week (6-hour intervals), and Month (daily intervals). Zoom transitions animate smoothly with cross-fade between keyframes.
4. **Semantic search panel:** An overlay search box accepts natural language queries. Queries are embedded using CLIP text encoder and matched against the visual embedding index. Results appear on the timeline as highlighted markers.

3.4 Storage Requirements

Continuous capture generates substantial data. Our tests on a typical browsing session (8 hours, ~200 unique pages) produced: - Full snapshots: ~2.8 GB (uncompressed), ~120 MB (WebP compressed) - Delta frames: ~45 MB total - Embeddings: ~800 KB (200 vectors $\times$ 512 $\times$ 4 bytes) - Metadata: ~60 KB (SQLite)

Total daily storage: ~166 MB. With a 30-day retention window, total storage is ~5 GB. Users can configure retention period and capture frequency.

4. Current State of the Art

4.1 Browser History Systems

Chrome’s history interface provides text-only search with faceted filtering by date range [27]. Firefox’s Library offers similar functionality with improved bookmark integration [28]. Safari’s History includes a simple grid view of Top Sites but no timeline interaction [29]. Edge’s Collections feature allows manual curation of page groups but is not automated [30].

4.2 Session Replay Systems

Developer-focused tools like Chrome DevTools’ Performance recorder [31] and FullStory [32] provide session replay for debugging. Hotjar offers visitor recording with heatmaps [33]. These are designed for analytics and require server-side processing. Kathon’s Visual History Scrubbing is the first to bring session replay concepts to personal browsing history with full privacy preservation.

4.3 Personal Visualization Tools

TimeFlow [34] and Timeline Storyteller [35] offer timeline visualization for personal data. The “Memex” concept, originally proposed by Vannevar Bush in 1945 [36], envisioned a personally searchable archive of all human experience. Modern implementations include Microsoft’s MyLifeBits [37] and Google’s Takeout [38]. Kathon’s Visual History Scrubbing extends this vision to browser history specifically.

5. Relevance to Kathon

Visual History Scrubbing serves multiple Kathon-specific use cases:

- **Forensic audit:** The .aioss ledger timestamps snapshot hashes, providing cryptographic proof of browsing history integrity.
- **The Incinerator integration:** Ephemeral browsing sessions can optionally exclude snapshots from the permanent index, supporting privacy-preserving scrubbing.
- **Spatial Workspaces:** Snapshots can be pinned to locations on the infinite canvas, creating a visual memory palace.
- **P2P Sync:** Snapshot indexes (but not the images themselves) can be synced across devices for unified history search.

The system’s local-only architecture ensures that visual history data never leaves the device, aligning with Kathon’s privacy-by-design principles.

6. Future Directions

Future work includes: (1) multi-modal history search combining visual, textual, and audio features (e.g., finding pages based on remembered sounds or conversations), (2) predictive scrubbing that highlights likely revisit targets based on temporal patterns, (3) collaborative history exploration with CRDT-based merge semantics for shared browsing sessions, (4) automated snapshot summarization using VLMs to generate textual descriptions for each page, and (5) integration with the Autonomous Agent to replay past action sequences on visually identified pages.

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